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Federal Department of the Environment, Transport, Energy and Communications DETEC

Swiss Federal Office of Energy SFOE
Energy Research and Cleantech Division

Interim report dated 14.01.2021

Positive Gap

Numerical approach for identifying the most effective low-cost optimization measures leading to more energy-efficient buildings

Source: Energo database

Scuola universitaria professionale della Svizzera italiana
Dipartimento ambiente costruzioni e design
Istituto sostenibilità applicata all'ambiente costruito

SUPSI

energo®
Efficienza energetica
per edifici

Date: 14.01.2021

Location: Bern

Publisher:
Swiss Federal Office of Energy SFOE
Energy Research and Cleantech
CH-3003 Bern
www.bfe.admin.ch

Subsidy recipients:
ISAAC – Istituto di Sostenibilità Applicata all'Ambiente Costruito
Campus Trevano CH-6952 Canobbio
https://www.supsi.ch/isaac

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SFOE contract number: SI/501937-01

Zusammenfassung

Invasive energetische Sanierungsansätze an Wohngebäuden sind oft anspruchsvoll in Bezug auf Anfangsinvestitionen und Umsetzungszeit, während schnelle und wirtschaftliche Energieoptimierungsmaßnahmen meist eine attraktivere und machbarere Strategie darstellen. Daher ist eine quantitative Studie erforderlich, um die Maßnahmen zu identifizieren, die unter Berücksichtigung variabler Wetterbedingungen zu den höchsten Energieeinsparungen führen. In dieser Arbeit wird ein künstliches neuronales Netzwerk über einen vom Energo-Verband zur Verfügung gestellten Datensatz trainiert und die komplexe Beziehung "Optimierungsmaßnahmen-Energieeinsparung" als Blackbox modelliert. Sensitivitätsindizes werden durch das trainierte Netzwerk berechnet, um den Einfluss jeder Maßnahme auf die Variabilität des Energieverbrauchs zu analysieren und zu quantifizieren, wobei gegenseitige Wechselwirkungen berücksichtigt werden.

Das trainierte Surrogatmodell liefert hochgenaue Vorhersagen der Energieeinsparungen ausgehend von den Wetterbedingungen und dem Vektor der angewandten Optimierungsmaßnahmen innerhalb des analysierten Zeitfensters. Darüber hinaus wurden die Sensitivitätsindizes mit verschiedenen Methoden berechnet, um vergleichbare Endwerte zu erhalten, was die Robustheit der Ergebnisse noch mehr beweist.

Zusammenfassend beschreibt die Studie eine Methodik, die auf der Anwendung von Surrogatmodellen basiert, mit dem Ziel, die effektivsten Energieoptimierungsmaßnahmen zu identifizieren, die die Definition von effizienteren und wirtschaftlicheren Wartungsplänen ermöglichen.

Résumé

Les approches de rénovation énergétique invasive sur les bâtiments résidentiels sont souvent exigeantes en termes d'investissement initial et de temps de mise en œuvre, tandis que les mesures d'optimisation énergétique rapides et économiques représentent la plupart du temps une stratégie plus efficace et réalisable. Il est pourtant très intéréssant analyser ce type de mésures sur le plan quantitive afin d’identifier l'ensemble des actions conduisant aux économies d'énergie les plus importantes compte tenu de certains conditions. Dans cette étude de recherche, un réseau de neurons artificiel est développé sur un ensemble de données fournies par l'association Energo, et la relation complexe "Mesures d'optimisation - Économies d'énergie" est modélisée sous forme de « black boxe ». Des indices de sensibilité sont calculés par le réseau formé pour analyser et quantifier l'influence de chaque mesure sur la variabilité de la consommation d'énergie, en tenant compte des interactions mutuelles.

Le meta-modèle d’apprentissage fournit des prévisions très précises sur les économies d'énergie à partir des conditions météorologiques et du vecteur des mesures d'optimisation appliquées dans la fenêtre temporelle analysée. De plus, les indices de sensibilité ont été calculés par différentes méthodologies, ce qui a permis d'obtenir des classements finaux comparables, prouvant ainsi la robustesse des résultats.

En conclusion, l'étude décrit une méthodologie basée sur l'adoption de meta-modèle dans le but d'identifier les mesures d'optimisation énergétique les plus efficaces permettant la définition de plans de maintenance plus performantes et plus économiques.

Summary

Invasive energy retrofitting approaches on residential buildings are often demanding in terms of initial investment and implementation time, while fast and economic energy optimization measures represent most of the time a more attractive and feasible strategy. A quantitative study is therefore needed to identify the set of actions leading to the highest energy savings accounting for variable weather conditions. In this work, an Artificial Neural Network is trained over a dataset provided by the Energo association, and the complex relation "Optimization measures-Energy Saving" is modeled as black-box. Sensitivity indexes are computed through the trained network to analyze and quantify the influence of each measure on the variability of the energy consumption, accounting for mutual interactions.

The trained surrogate model provides highly accurate predictions of the energy savings starting from the weather conditions and the vector of applied optimization measures within the analyzed time-window. Moreover, the sensitivity indexes have been computed through different methodologies obtaining comparable final rankings, proving even more the robustness of the results.

In conclusion, the study describes a methodology based on the adoption of surrogate models with the aim of identifying the most effective energy optimization measures allowing the definition of more efficient and economic maintenance plans.

Contents

Abbreviations

LICOM - Low-investment cost optimization measures

CECE - Cantonal energy performance certificate for buildings

EPG - Energy performance gap

ANN – Artificial neural network

ES – Energy saving

GSA – Global sensitivity analysis

PMF – Probability mass function

EASI - Effective algorithm sensitivity indices

1 Introduction

1.1 Background information and current situation

The Positive Gap Project is part of a wider series of studies and research projects developed by SUPSI in collaboration with other organizations operating on the national territory. In particular, it is worth mentioning that many activities, carried out by SUPSI and the Energo Association, aim at the development of new methodologies for monitoring and for reaching a more effective energy optimization. The GAPxPLORE project developed between 2017 and 2019 in collaboration with the University of Geneva and the Minergie, CECE and Energo Associations, represents one clear example of this specified line of research

Thanks to the GAPxPLORE project it has been possible to analyze the energy performance gap (EPG) between measured and calculated energy consumption in the Swiss residential sector. This project confirmed the existence of a significant EPG in the Swiss residential sector, depending on the thermal quality of the building. It was also possible to quantify the EPG by defining median, maximum and minimum values according to the type of building.

The quoted study also highlighted limitations such as the nature of the energy values that are compared (the type of energy consumption, weighting factors adopted, etc.). Besides, it was particularly difficult to evaluate energy consumption based on different approaches and databases.

Starting from the results obtained from previous research activities, the characterization of the EPG must be able to be detailed on the basis of energy consumption monitored continuously and systematically. The focus in this perspective shifts to the operational phase of the building, during which consumption can be optimized, regardless of the initially estimated theoretical consumption.

1.2 Purpose of the project

The building stock represents one of the main contributions to the final Swiss national energy demand. The widespread adoption of less efficient heating supply systems, coupled with a low level of optimal maintenance strategies, leads to a large potential for energy consumption reduction.

An invasive retrofitting approach aimed at increasing the energy efficiency, such as the building envelope renovation or replacement of an energy plant, is often demanding in terms of initial investment and implementation time. In this case, the payback time of the energy-saving investment is often longer than the lifetime of the element, hence why most of the times, low-investment cost optimization measures (LICOM) represent a more attractive and feasible strategy to reduce energy consumption in buildings while ensuring a profitable return on investment.

The LICOM effectiveness can be quantified through the concept of *performance gap* [1] that refers to the difference in terms of energy consumptions between the measured and the predicted value, this last quantified through a theoretical approach. Therefore, the adoption of specific LICOMs should affect the frequency of occurrence and the magnitude of *positive performance gaps* by improving the overall efficiency if compared to the predicted (computed) trend.

A quantitative study is therefore required to identify the LICOMs leading to the highest energy savings by accounting at the same time for the effects of different weather conditions. Indeed, particular climatic conditions can affect the building stock's energy consumption regardless of the selected set of LICOMs.

1.3 Objectives and methods

The identification of a robust ranking associated with the analyzed LICOMs represents a challenging computational task under multiple points of view.

To increase the robustness of the results the applied methodology should be based on a sufficiently large dataset of consistent energy consumption records, adopted LICOMs and weather indicators, referring to well-tracked building stock. Moreover, the employed data must cover the longest possible time-window in order to account for multiple boundary conditions that can differently affect the final figures.

The data collection task has been completed thanks to the collaboration with the Energo association, whose energy consumption monitoring activity allows the acquisition of continuative data on different building complexes with the list of performed LICOMs.

Once the required dataset is defined, a preliminary analysis must be carried out to identify vectors of intermediate time-windows in which compute the total energy savings and the corresponding set of applied LICOMs. In this regard, multiple LICOMs are often adopted within the same time-window, hence why a more advanced computational approach is needed to quantify the contribution of each of them to the final output of interest.

In the presented work, an artificial neural network (ANN) [2] is employed to model and analyze the complex relation "LICOM-Energy saving". Indeed, correlation coefficients cannot be derived directly from the initial dataset since the energy consumption in a fixed time-window is simultaneously affected by multiple LICOMs and no assumptions can be adopted due to the lack of studies in the technical literature aiming at characterizing this phenomenon. Moreover, thanks to the capacity of the validated ANN to model separately each input-output function, it can be efficiently employed to perform advanced sensitivity analyses by creating synthetic data.

Sensitivity indexes [3] are computed to quantify the influence of each input on the variability of the analyzed output. In this regard, different computational strategies will be explored in the next stage to provide more robust and meaningful results. Indeed, the variance of each input can be both taken into account or not depending on the variable type and besides, the interactions between variables can affect in different ways the possible effectiveness of each studied LICOM, hence why they should be accounted for within the analysis.

2 Description of facility

To characterize the dependencies between optimization measures and energy savings, a residential building stock of 92 units located in the canton Geneva is selected. In particular, the analyzed building stock is characterized by a consistent dataset of consumption and optimization data for a time window of a minimum of three years.

The activity of data structuring, cleaning and filtering is based on the master thesis [4] and the energy savings this project is focused on are due to ensure heating and hot water, mainly because these represent the most reliable data. Positive and negative energy savings are structured in a specific dataset in which the following information is listed:

- Start Date of the event
- End Date of the event
- Performance gap
- Economic gap
- ID building

The optimization measures undertaken on the followed building stock are reported in a different dataset, with the following main data fields:

- Date
- Description of the measures
- Cluster
- ID building

The selected building stock allows obtaining well-populated and coherent data within a global time window of around 4 years. More specifically, a total of almost 5000 energy consumption events can be obtained from the dataset, even if all the observations have to be furtherly grouped by a reduced time window defined to properly account for both causes and effects. Additional details on the adopted methodology will be provided in the next sections.

Furthermore, to account for the influence of the weather conditions on the variation of the energy savings, an additional dataset is employed within the analyses chain. This allows for reaching more robust results able to separate the effects of the weather conditions from the contribution of the optimization measures.

- Temperature
- Wind Speed
- Humidity
- Rainfall

The daily average of each parameter is exported from the archive of the MeteoSwiss ground-level monitoring networks, through the IDAWEB[1] web platform.

[1] https://gate.meteoswiss.ch/idaweb

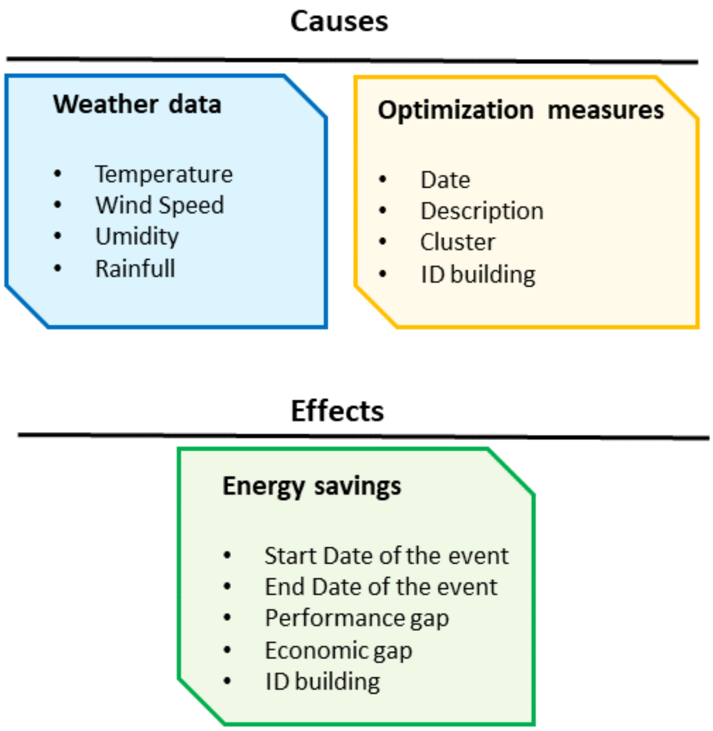

Figure 1 Data analyzed

2.1 Optimization measures and clustering

The heterogeneity of the possible optimization measures requires the definition of a set of predefined classes based on which the whole numerical analysis can be performed. In this regard, a total of 63 classes [4] are adopted in this work. They are listed in Table 1 and can be grouped into nine main categories.

Table 1 List of analyzed LICOMs

LICOM	DESCRIPTION	LICOM	DESCRIPTION
'BOILER_CHANGE'	Boiler change	'HW_T_GUIDE_NIGHT'	Hot water night guide temperature
'BURNER_OPT'	Burner power adjustment	'HW_T_METER_CHANGE'	Hot water sensor position change
'FURNACE_1_OFF'	Interruption of one furnace during summer	'HW_T_OFF'	Hot water heating temperature stop
'FURNACE_CHANGE'	Furnace change	'HW_T_ON'	Hot water heating temperature start
'FURNACE_OPT'	Furnace cascade optimization	MAINT_SOLAR'	Thermal solar installation maintenance

'HEATING_CIRC_TIME'	Heating circular schedule	'REGUL_AUTO'	Regulation system on AUTO mode
'HEATING_CURVE'	Heating curve slope change	'REGUL_CHANGE'	Regulation system change
'HEATING_CURVE_HIGH'	Upper heating curve change	'REGUL_MANU'	Regulation system on MANUAL mode
'HEATING_CURVE_LOW'	Lower heating curve modification	'REGUL_T'	Setpoint temperature
'HEATING_CURVE_PARALLEL'	Parallel heating curve modification	'REGUL_THERM_VALVE_CHANGE'	Thermostatic valves change
'HEATING_HYST'	Heating hysteresis modification	'REGUL_TIME'	Heating time
'HEATING_LIFTING'	Heating lifting temperature change	REGUL_T_FURNACE'	Setpoint furnace temperature
'HEATING_NIGHT_LOWERING'	Heating night lowering	'REGUL_T_DAY'	Day setpoint temperature
'HEATING_OFF'	Heating interruption	'REGUL_T_DAY_ECO'	Day ECO setpoint temperature
'HEATING_ON'	Heating start	'REGUL_T_MAIN'	Main setpoint temperature
'HEATING_T_OFF'	Heating interruption temperature	'REGUL_T_MAX_AERO'	Maximum aerotherm temperature
'HEAT_CIRC_CHANGE'	Hot water circulator change	REGUL_T_MAX_BOILER'	Maximum boiler setpoint temperature
'HEAT_CIRC_POWER'	Hot water circulator power	'REGUL_T_MIN_BOILER'	Minimum boiler setpoint temperature
'HEAT_HYDRO_BALANCE'	Hydraulic balance	'REGUL_T_NIGHT'	Night setpoint temperature
'HEAT_MAINT'	Maintenance work of heating system	'REGUL_T_NIGHT_ECO'	Night ECO setpoint temperature
'HEAT_RAD_INSUL'	Radiator pipes insulation	'REGUL_T_NIGHT_OFF'	Night heating interruption setpoint temperature
'HEAT_TIME_CONST'	Heating time constant	'REGUL_T_NIGHT_ON'	Night heating start setpoint temperature
'HW_CIRC_CHANGE'	Hot water circulator change	'REGUL_T_OFF'	Heating interruption setpoint temperature
'HW_CIRC_POWER'	Hot water circulator power	'REGUL_T_ON'	Heating start setpoint temperature
'HW_HYST'	Hot water hysteresis change/interlocking differential	REGUL_WINTER_MODE'	Winter Mode modification
'HW_LIFTING'	Hot water-lifting temperature change	'VENTIL_GV'	High-speed ventilation schedule
'HW_MAINT'	Hot water system maintenance	'VENTIL_HC'	Ventilation heating curve
'HW_PUMP_AUTO'	Hot water circulator pump on AUTO mode	'VENTIL_HEAT_ROOM'	Ventilation opening in the heating curve

'HW_TIME'	Hot water circulation schedule	'VENTIL_PV'	Low-speed ventilation schedule
'HW_TIME_LOAD'	Hot water load schedule	'OTHER'	Special and/or specific optimization measures of particular systems, or which do not enter into one of the previous categories
'HW_T_GUIDE'	Hot water guide temperature		
'HW_T_GUIDE_DAY'	Hot water day guide temperature		

Category

- Furnace optimization
- Hot water
- Heating day-night setpoint temperature
- Heating schedule
- Furnace setpoint temperature
- Heating curve optimization
- Maintenance
- Regulation system optimization
- Additional heating optimization

3 Procedures and methodology

The adopted approach is based on an ANN by wich sensitivity indexes are computed to quantify the relevance of each optimization measure on the energy consumption of the whole building stock. The data-driven methodology needs of a preliminary stage for the filtering and cleaning of the collected data, required for the definition of a suitable training dataset for the calibration of the selected surrogate model. The quantification of sensitivity indexes is followed by a critical analysis as well, in order to provide a more practical results interpretation. Pre and post-processing stages are therefore necessary (Figure 2) both to calibrate the inputs for the proposed computational approach and to extract the main quantitative findings from the final numerical results.

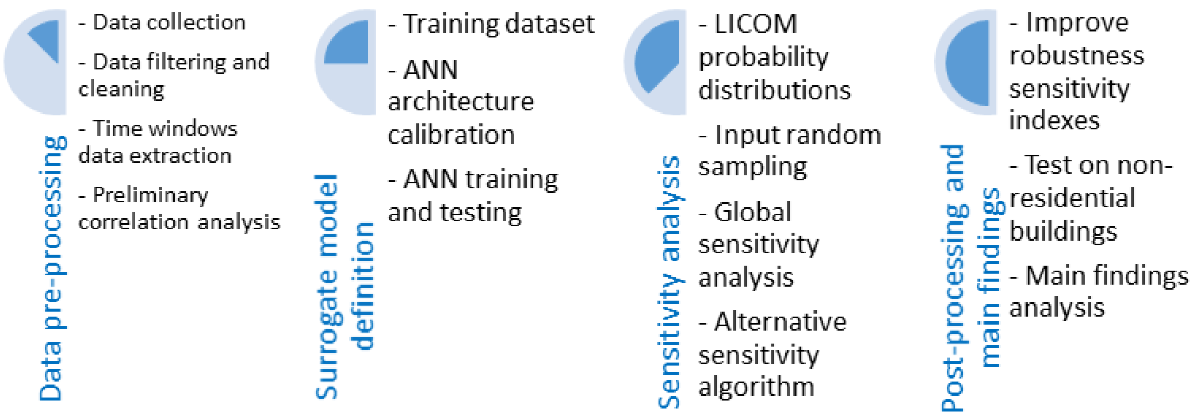

Figure 2 Main project stages

3.1 Correlation analysis

A preliminary study is carried out by computing the correlation between a quantitative measure of the consumption energy savings (ES) and the employed classes of optimization measures (OM). The numerical analysis is performed by identifying only one time-window ΔT_s, by which the global period of analysis ΔT is divided. Therefore, a total of $\Delta T/\Delta T_s$ observations are obtained and for each one both the causes and effects are identified in ΔT_s. The computed correlation is affected by the selected ΔT_s, since different intermediate time-windows correspond to different OM frequency vectors Ξ and ESs. Hence why a correlation vector is computed for each identified optimization measure by varying the corresponding ΔT_s. The median value of each distribution is extrapolated, together with the associated variance, in order to provide a more robust preliminary assessment of the most important measures. As previously specified, this numerical approach is not able to account for the inputs overlapping

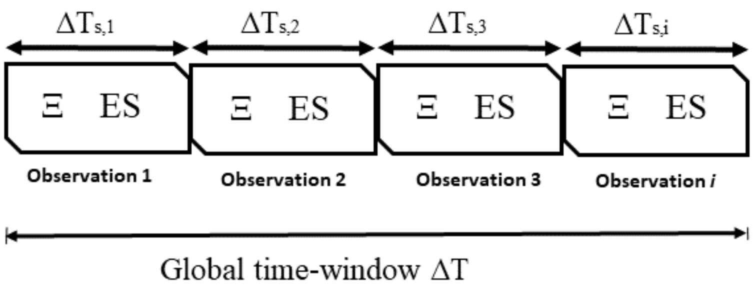

Figure 3 Global time-window structure for the correlation analysis

phenomenon, and more advanced methodologies are required to account for more complex interactions. Moreover, the accuracy of the obtained correlation vector is reduced due to the missed differentiation in terms of time-windows between input (Ξ) and output (ES).

3.2 Surrogate model

A more advanced numerical methodology is required to model complex interactions between the problem inputs. Metamodel based approaches [5,6] can capture more insights from black-box models and are therefore suitable for analyzing hidden non-linear interdependencies.

3.2.1. ANN

Over the past years, ANNs have experienced a relevant growth in popularity thanks to their easy implementation and flexibility linked with the capability of learning complex and non-linear relations within the analyzed problem. In general, the structure of an ANN tries to simulate the human brain network of neurons. More specifically, we can identify three different typologies of nodes, namely, input – hidden – output node, as shown in Figure 4. In addition to an input and output layer, we can have one or more hidden layers that increase the network capability of modeling high non-linear input-output patterns.

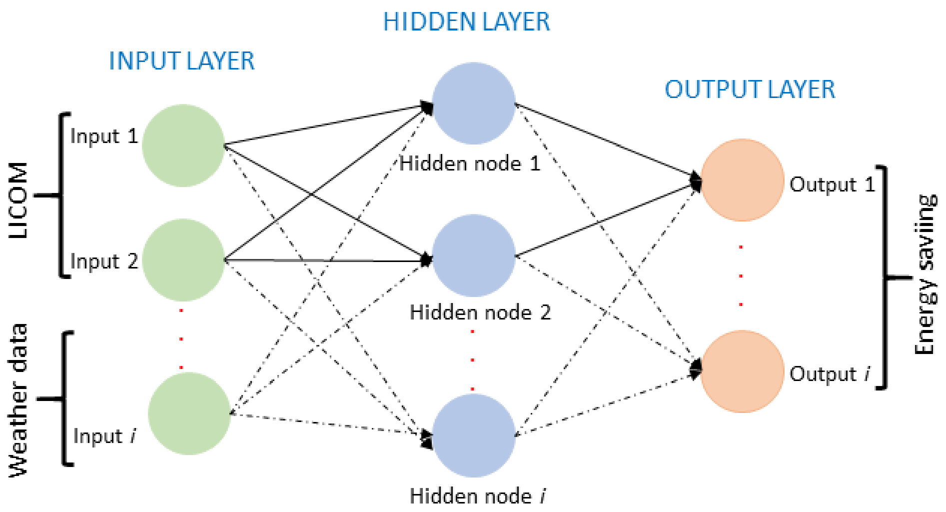

Figure 4 ANN structure

Thus, the ANN is characterized by a set of nodes (or neurons) that can be distributed on a single hidden layer or more (deep learning problems). Each neuron z_h, in the hidden layer *h*, receives one or more inputs *x* that are multiplied by proper weights *w* (connections in Figure 4) and simply summed before feeding the neuron. Below its mathematical formulation:

$$z_h = \sum_{p=1}^{n_i} w_{hp} \cdot x_p + b_h \qquad 1$$

where n_i represents the number of inputs, while b_h is the bias term. The non-linearity of the input-output relation is taken into account by the so-called activation function. Different activation functions can be adopted, the one used for this study is the hyperbolic tangent sigmoid, that is continuous, differentiable and bounded between 1 and -1. In case of one single hidden layer, the input data go through the first hidden activation function for each hidden neuron and then they are processed by another activation function to produce the final prediction y_t.

In case of a supervised problem, the learning process aims at tuning the weights parameters in order to minimize the square of the residuals between the predicted values $\hat{y}_t$ and the training data y_t:

$$L = \frac{1}{n} \cdot \sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \qquad 2$$

with n equal to the cardinality of the training dataset. In this regard, the back-propagation algorithm represents a key element of the training stage since it allows computing the partial derivative of the loss function L for every weight and bias of the network and thus the adoption of a gradient-based optimization algorithm. For further details on the learning process refer to [2].

3.2.2. Time-window based approach

The adopted numerical approach requires the definition of four different time windows to extract data from each dataset, namely:

- **ΔT_0** - Time-window to shift each observation
- **ΔT_1** - Time-window for the screening of optimization measures
- **ΔT_2** - Time-window for the screening of the energy savings and weather data
- **ΔT** – Global time-window of analysis

The use of a different time-window for each specific optimization measure does not lead to a feasible numerical approach. Hence, the proposed methodology is based on a three-dimensional time-window vector, $\Gamma=[\Delta T_0, \Delta T_1, \Delta T_2]$, that is employed to compute the frequency vectors Ξ; the data weather vector Θ; and the corresponding *ES*, respectively. More specifically, as shown in Figure 5, each i-th observation of the training dataset is defined by computing Ξ over the input vector ΔT_1; while Θ and the corresponding energy savings over ΔT_2. Figure 6 reports for example the normalized vectors Θ and *ES* for a specific Γ.

Moreover, each observation is temporally shifted of ΔT_0, this allows increasing the dimension of the training dataset without including duplications. The total time-window of analysis can be computed as follow:

$$\Delta T = n \cdot \Delta T_0 + \Delta T_1 + \Delta T_2 \qquad 3$$

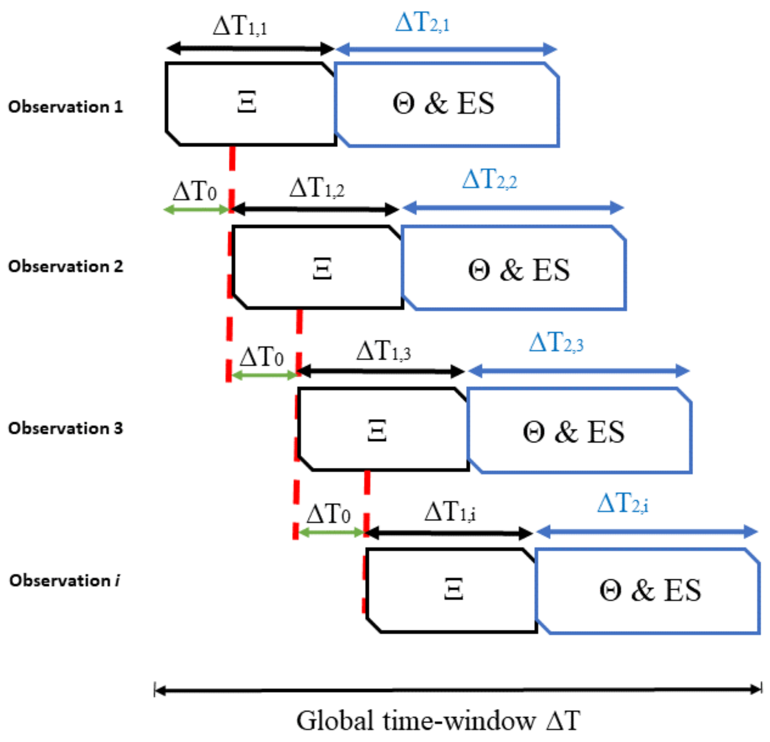

Figure 5 Time-windows scheme

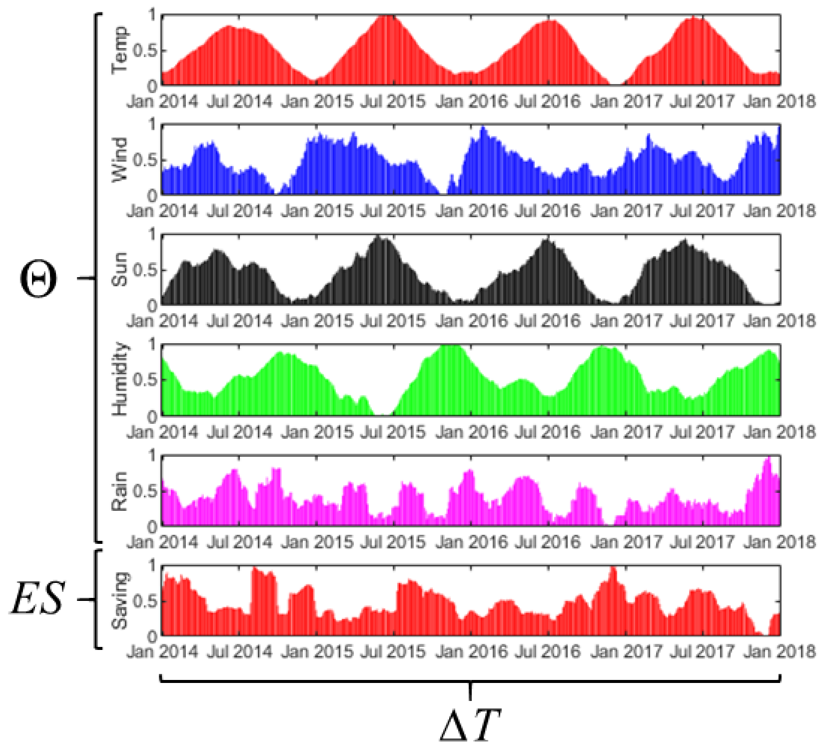

Figure 6 Θ and ES vectors for a selected time-window

In particular, since ΔT_1 and ΔT_2 (a few days) are negligible with respect to the total ΔT (years) the ratio $\frac{\Delta T}{\Delta T_0} \approx n$ is almost equal to the total number of observations.

3.3 Sensitivity analysis

In this section, a brief introduction to global sensitivity analysis (GSA) [3] is carried out.
The GSA is based on a decomposition of the variance of each output parameter resulting from variations of the input parameters x_i, i=1,2,..N in the range of interest.
Let Y be the output of a deterministic model $f(X)$. Assuming mutually independent inputs, the variance of Y can be expressed as [7]:

$$Var(Y) = \sum_{i=1}^{d} D_i(Y) + \sum_{i<j}^{d} D_{ij}(Y) + \cdots + D_{12\ldots d}(Y) \quad 4$$

where $D(Y) = Var[E(Y \mid X_i)]$ and $D_{ij} = Var[E(Y \mid X_i, X_j)] - D_i(Y) - D_j(Y)$. The first order Sobol' indexes express the contribution of each input i on the output variance and can be calculated as:

$$S_i = \frac{D_i(Y)}{Var(Y)} \quad 5$$

In addition, when the problem dimensionality d increases, the so-called total indexes [3] can be introduced to account also for interactions effects:

$$S_{T_i} = S_i + \sum_{i<j} S_{ij} + \sum_{j\neq i, k\neq i, j<k} S_{ijk} + \cdots = \sum_{l \in \phi} S_l \quad 6$$

where ϕ represents all the possible input combinations and $S_{ij} = D_{ij}(Y)/Var(Y)$.
The training dataset is employed to define a set of discrete probability mass functions (PMFs) based on which the artificial dataset for sensitivity analyses is generated. For example, Figure 7 shows the PMFs associated with nine analyzed optimization measures. The probability of occurrence of each LICOM within the selected time window ΔT_1 is reported, thus by modifying ΔT_1 the discrete probability will change accordingly.
Unfortunately, the use of a single optimal ANN for computing sensitivity indexes leads to reduced robustness in the results. This is due to the uncertainty that affects the surrogate model calibration coming from both architecture definition and weights initialization. To account for this drawback a set of multiple ANNs is adopted to compute a distribution of sensitivity indexes associated with each LICOM. It is worth specifying that the training and calibration stage of surrogate models always lead to epistemic uncertainty due, for instance, to the selection of the optimal hyperparameters.

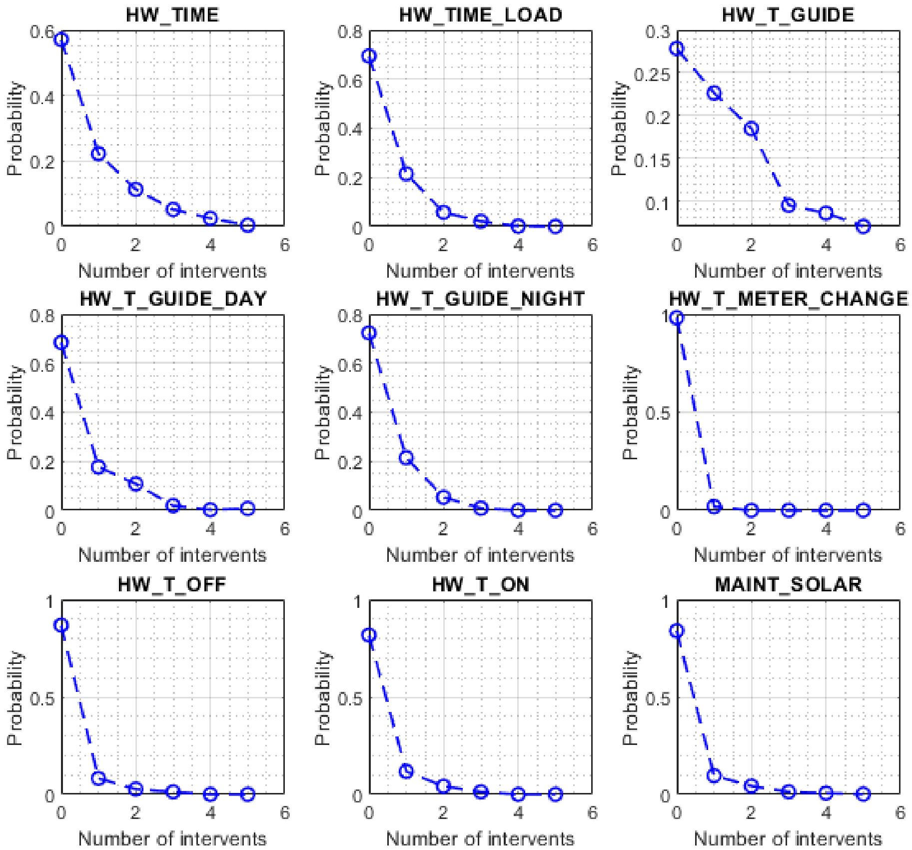

Figure 7 PMFs associate with nine LICOMs

4 Activities and results

The definition of a training dataset, starting from a row database of LICOMs and energy consumptions, requires the adoption of a specific vector Γ. In this regard, ΔT_0, ΔT_1 and ΔT_2 should be selected trying to capture as many as possible LICOMs in ΔT_1 and coherent corresponding effects in ΔT_2, increasing at the same time ΔT_0. A grid search approach is employed to tune the vector Γ by maximizing the accuracy of the network. Figure 8 shows the evolution of the coefficient of determination R^2 obtained by exploring multiple combinations of ΔT_0, ΔT_1 and ΔT_2. Finally, the vector Γ has been selected considering these results combined with expert elicitation (Table 2)

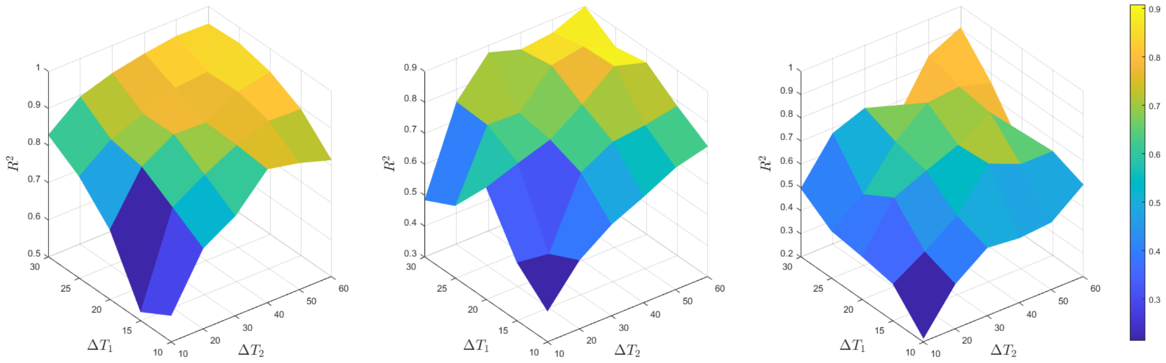

Figure 8 Vector Γ calibration

ΔT_0	ΔT_1	ΔT_2
2 days	15 days	30 days

Table 2 Vector Γ adopted for the analysis

The global time window ΔT (Equation 3) for the training dataset definition goes from the beginning of 2013 to the end of 2018, for a total of 2191 days and around 1100 observations.

Table 3 provides statistical details on the occurrences of each LICOM considering five different time-windows. It is clear how the majority of the measures show a relatively low frequency (less than one occurrence per ΔT), even increasing the associated time-window. Moreover, the high standard deviations indicate that the LICOMs are highly sparse, increasing the difficulty in analyzing the relative effectiveness. Finally, the mean and standard deviations of the energy-saving reported in Table 3 are computed in a time-window translated of ΔT with respect to the LICOM.

Time window [days]	**20**		**40**		**60**		**80**		**100**	
LICOM	**Occurrences**									
	Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
'BOILER_CHANGE'	0.039	0.253	0.079	0.359	0.080	0.400	0.158	0.501	0.214	0.516
'BURNER_OPT'	0.390	0.672	0.763	1.025	1.160	1.491	1.526	1.611	2.143	1.792
'FURNACE_1_OFF'	0.104	0.307	0.211	0.474	0.320	0.557	0.421	0.769	0.571	0.640
'FURNACE_CHANGE'	0.065	0.248	0.132	0.343	0.200	0.408	0.263	0.562	0.357	0.488
'FURNACE_OPT'	0.299	0.630	0.605	1.001	0.920	1.382	1.211	1.584	1.643	1.727
'HEATING_CIRC_TIME'	0.052	0.276	0.105	0.388	0.120	0.440	0.211	0.535	0.286	0.561
'HEATING_CURVE'	6.026	7.090	11.947	11.779	17.800	17.325	23.895	21.008	33.143	25.376
'HEATING_CURVE_HIGH'	0.818	1.604	1.632	2.665	2.400	3.629	3.263	4.544	4.500	5.682
'HEATING_CURVE_LOW'	0.766	1.413	1.447	2.226	2.200	3.000	2.895	4.081	4.214	4.865
'HEATING_CURVE_PARALLEL'	0.584	1.239	1.184	1.768	1.720	2.283	2.368	2.499	3.214	2.722
'HEATING_HYST'	0.026	0.160	0.053	0.226	0.080	0.400	0.105	0.459	0.143	0.352
'HEATING_LIFTING'	0.208	0.468	0.368	0.675	0.560	0.870	0.737	0.933	1.143	1.280
'HEATING_NIGHT_LOWERING'	0.026	0.160	0.053	0.324	0.080	0.400	0.105	0.459	0.143	0.352
'HEATING_OFF'	0.312	1.195	0.632	1.746	0.960	2.111	1.263	2.353	1.714	2.384

'HEATING_ON'	0.273	1.284	0.553	1.796	0.840	2.173	1.105	2.447	1.500	2.694
'HEATING_T_OFF'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'HEAT_CIRC_CHANGE'	0.039	0.195	0.079	0.273	0.120	0.332	0.158	0.375	0.214	0.414
'HEAT_CIRC_POWER'	0.429	1.409	0.868	2.673	1.320	3.262	1.737	3.739	2.357	3.364
'HEAT_HYDRO_BALANCE'	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
'HEAT_MAINT'	0.247	0.517	0.500	0.726	0.760	0.970	1.000	1.054	1.357	1.710
'HEAT_RAD_INSUL'	0.013	0.114	0.026	0.162	0.040	0.200	0.053	0.229	0.071	0.258
'HEAT_TIME_CONST'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'HW_CIRC_CHANGE'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'HW_CIRC_POWER'	0.130	0.817	0.263	1.155	0.400	1.443	0.526	1.645	0.714	1.839
'HW_HYST'	0.390	0.876	0.789	1.492	1.200	1.414	1.579	1.953	2.143	1.558
'HW_LIFTING'	0.312	0.782	0.605	1.220	0.920	1.412	1.211	1.751	1.714	2.031
'HW_MAINT'	0.078	0.315	0.158	0.437	0.160	0.374	0.316	0.582	0.429	0.458
'HW_PUMP_AUTO'	0.052	0.276	0.105	0.388	0.160	0.473	0.211	0.535	0.286	0.594
'HW_TIME'	1.156	1.702	2.289	3.153	3.400	2.872	4.579	4.312	6.357	4.271
'HW_TIME_LOAD'	0.714	1.394	1.395	2.553	2.080	2.100	2.789	3.425	3.929	3.091
'HW_T_GUIDE'	2.844	3.142	5.684	4.743	8.640	6.885	11.368	7.697	15.643	9.855
'HW_T_GUIDE_DAY'	0.662	0.982	1.342	1.599	2.040	2.226	2.684	2.730	3.643	3.203
'HW_T_GUIDE_NIGHT'	0.468	0.736	0.947	1.161	1.440	1.502	1.895	2.025	2.571	1.993
'HW_T_METER_CHANGE'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'HW_T_OFF'	0.299	0.762	0.526	1.246	0.800	1.190	1.053	1.747	1.643	1.877
'HW_T_ON'	0.416	0.937	0.816	1.608	1.240	1.763	1.632	2.060	2.286	2.314
'MAINT_SOLAR'	0.338	0.788	0.684	1.141	1.040	1.695	1.368	2.060	1.857	2.434
'OTHER'	1.000	1.298	1.947	2.053	2.880	2.862	3.895	3.230	5.500	4.586
'REGUL_AUTO'	0.117	0.396	0.237	0.590	0.320	0.627	0.474	0.772	0.643	0.990
'REGUL_CHANGE'	0.208	0.408	0.421	0.642	0.600	0.816	0.842	1.068	1.143	1.069
'REGUL_DAY'	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
'REGUL_MANU'	0.078	0.270	0.158	0.437	0.240	0.523	0.316	0.671	0.429	0.910
'REGUL_T'	13.948	14.758	27.158	22.957	40.720	31.490	54.316	36.748	76.714	51.657
'REGUL_THERM_VALVE_CHANGE'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'REGUL_TIME'	2.208	4.053	4.211	6.593	6.320	6.638	8.421	9.430	12.143	10.350
'REGUL_T_BOILER'	0.506	1.253	1.026	1.896	1.560	2.830	2.053	2.877	2.786	2.874
'REGUL_T_DAY'	4.247	4.843	8.342	7.778	12.320	10.703	16.684	13.941	23.357	16.822
'REGUL_T_DAY_ECO'	1.013	1.936	1.974	2.964	3.000	3.742	3.947	4.339	5.571	6.012
'REGUL_T_MAIN'	0.481	1.008	0.947	1.314	1.440	1.685	1.895	1.912	2.643	2.444
'REGUL_T_MAX_AERO'	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
'REGUL_T_MAX_BOILER'	0.377	0.946	0.763	1.731	1.160	1.491	1.526	2.294	2.071	1.792
'REGUL_T_MIN_BOILER'	0.130	0.469	0.263	0.644	0.400	0.866	0.526	0.964	0.714	1.543
'REGUL_T_NIGHT'	5.221	6.688	10.132	10.655	15.280	14.002	20.263	16.556	28.714	24.101
'REGUL_T_NIGHT_ECO'	1.273	2.275	2.579	3.422	3.920	4.453	5.158	4.729	7.000	6.947
'REGUL_T_NIGHT_OFF'	0.104	0.502	0.184	0.692	0.280	0.843	0.368	0.955	0.571	1.060
'REGUL_T_NIGHT_ON'	0.065	0.375	0.105	0.509	0.160	0.624	0.211	0.713	0.357	0.799

'REGUL_T_OFF'	0.312	0.977	0.579	1.388	0.880	1.787	1.158	1.979	1.714	2.748
'REGUL_T_ON'	0.104	0.528	0.158	0.679	0.240	0.831	0.316	0.946	0.571	1.056
'REGUL_WINTER-MODE'	0.104	0.416	0.211	0.577	0.320	0.748	0.421	0.838	0.571	0.990
'VENTIL_GV'	0.065	0.296	0.132	0.414	0.200	0.577	0.263	0.653	0.357	0.724
'VENTIL_HC'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'VENTIL_HEAT_ROOM'	0.078	0.270	0.158	0.370	0.240	0.523	0.316	0.582	0.429	0.828
'VENTIL_PV'	0.156	0.400	0.289	0.515	0.400	0.707	0.579	0.902	0.857	1.113
	Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
Energy saving [kWh]	195771	394576	326774	462162	461009	699454	587312	673102	724443	955076

Table 3 Statistical details on the LICOMs occurrence

4.1 Surrogate model calibration

The optimization of the ANN architecture follows a *Trial and error* approach. In particular, the number of hidden layers is fixed at one, on this regard many research works have shown how a single hidden layer is sufficient for a wide range of computational problems [e.g. 8,9], while the number of neurons is considered variable. The final configuration is therefore characterized by one layer, sixty-eight input neurons and fifty hidden neurons.

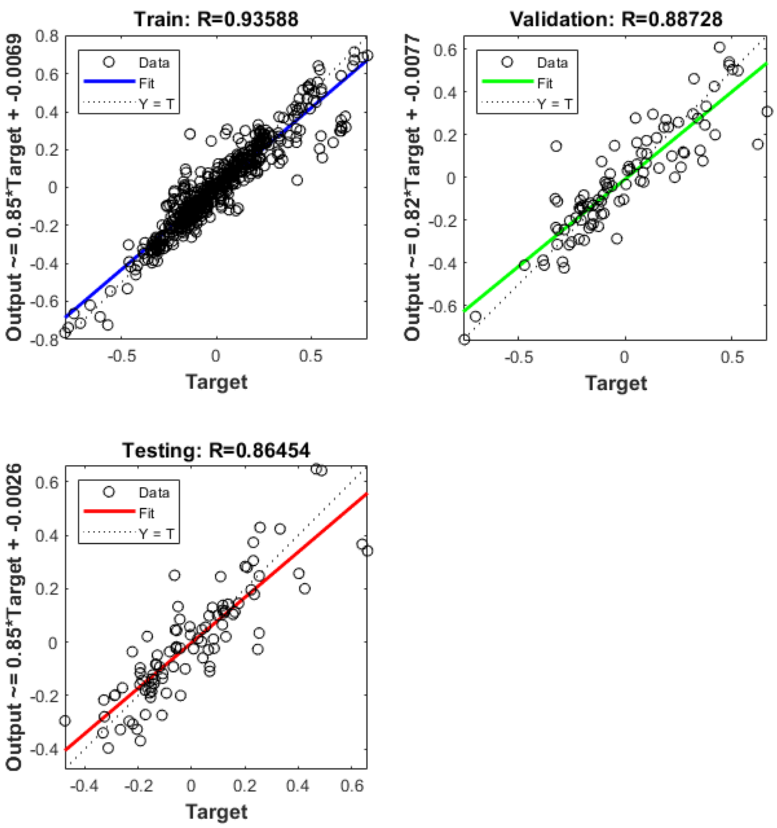

Figure 9 ANN performances in the training, test and validation stage

The training dataset is divided into three parts: 75% training, 12.5% validation and 12.5% test. Figure 9 reports the correlation coefficient R for each stage of the calibration process while Figure 10 shows a clear comparison between the test observations and the outputs predicted by the final ANN. Both graphs demonstrate the goodness of the adopted surrogate model for approximating the whole phenomenon.
The output energy saving is reported in a normalized form between -0.8 and 0.8 to standardize the different input units.

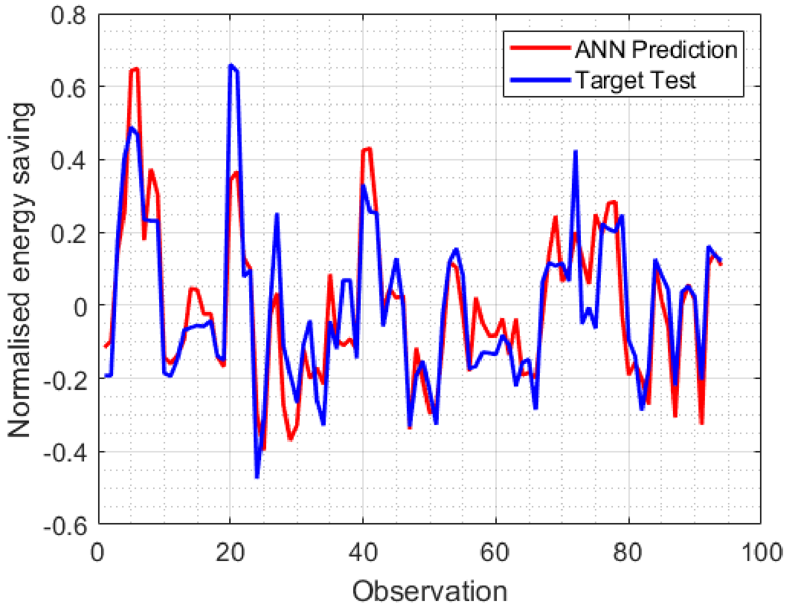

Figure 10 Comparison between ANN predictions and test observations

5 Evaluation of results to date

The robustness of the sensitivity analysis is affected by the uncertainty associated with the model architecture and the calibration process. More specifically, the weights in Equation 1 are randomly initialized before the optimization starts, leading to different accuracy even keeping the same ANN architecture.
In this regard, as discussed and proposed in [10], a set of optimal ANNs is defined and multiple sensitivity analyses are performed to identify a distribution of indexes for each LICOM. Figure 12 reports the mean and median values with the probability boxes defined by the 25th and the 75th percentiles.
A total of 150 ANNs are pre-selected and for each of them, a minimum of 10’000 scenarios is generated (each scenario is characterized by a set of applied LICOMs) for a total of model evaluations equal to $N = n * (M + 1)$. Considering 63 inputs (M) and 10’000 samples (n) the analysis requires 9,6*10^{6} model runs. Latin Hypercube Sampling method [11] is employed for the samples’ generation.

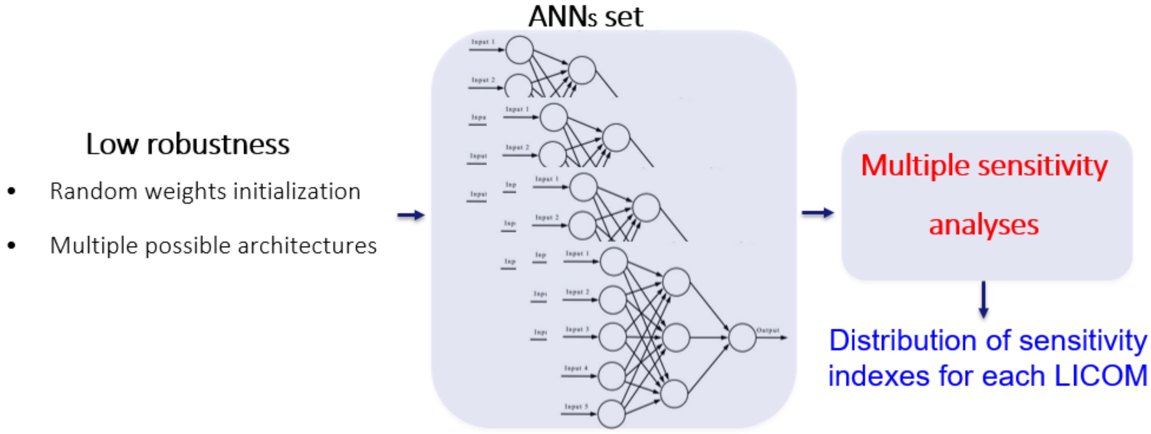

Figure 11 Distribution of sensitivity indexes by accounting for the uncertainty in the model definition

This approach turns out to be computationally expensive. For this reason, in this preliminary stage of the research project, the EASI approach is used to derive indexes from a given dataset of 50'000 model evaluations for each ANN. This algorithm is able to connect variance-based approaches with methods based on Monte-Carlo simulations [12].
The results in terms of correlation coefficients [13], defined in section 3.1, have shown low robustness and accuracy if compared with the results provided by the EASI method based on uncoupled LICOM' effects. From Figure 12 we can identify the top five median indexes:

1. REGUL_TIME
   Time in [h/day] when the heating is turned ON. This includes modifications of the day/night or week/weekend heating schedule. Example: 6h00-22h00 each day => 16 h/day.

2. *HW_T_OFF*
   Hot water heating temperature stop, in [°C]. Depending on the possibilities available to set the hot water temperature, it is possible to activate heating e.g. at 45°C (HW_T_ON) and switch off at 55°C (HW_T_OFF). By doing that the boiler use is improved, as well as the efficiency of the load of hot water, thus energy efficiency.

3. *HEATING_CURVE*
   Heating curve slope change. When heating a building, a heating curve is identified, meaning one chooses at which temperature water (for radiators, etc.) should be heated according to the outside temperature. E.g. with a slope of 1.5, for 10°C outside, water will be heated at 38°C, for -10°C outdoor temperature, water will be heated at 60°C. Thus, changes to heat curves allow playing with much delicacy with the mid-cold and cold weather conditions. Changes in heating curves could be the slope, angle, or parallel shift.

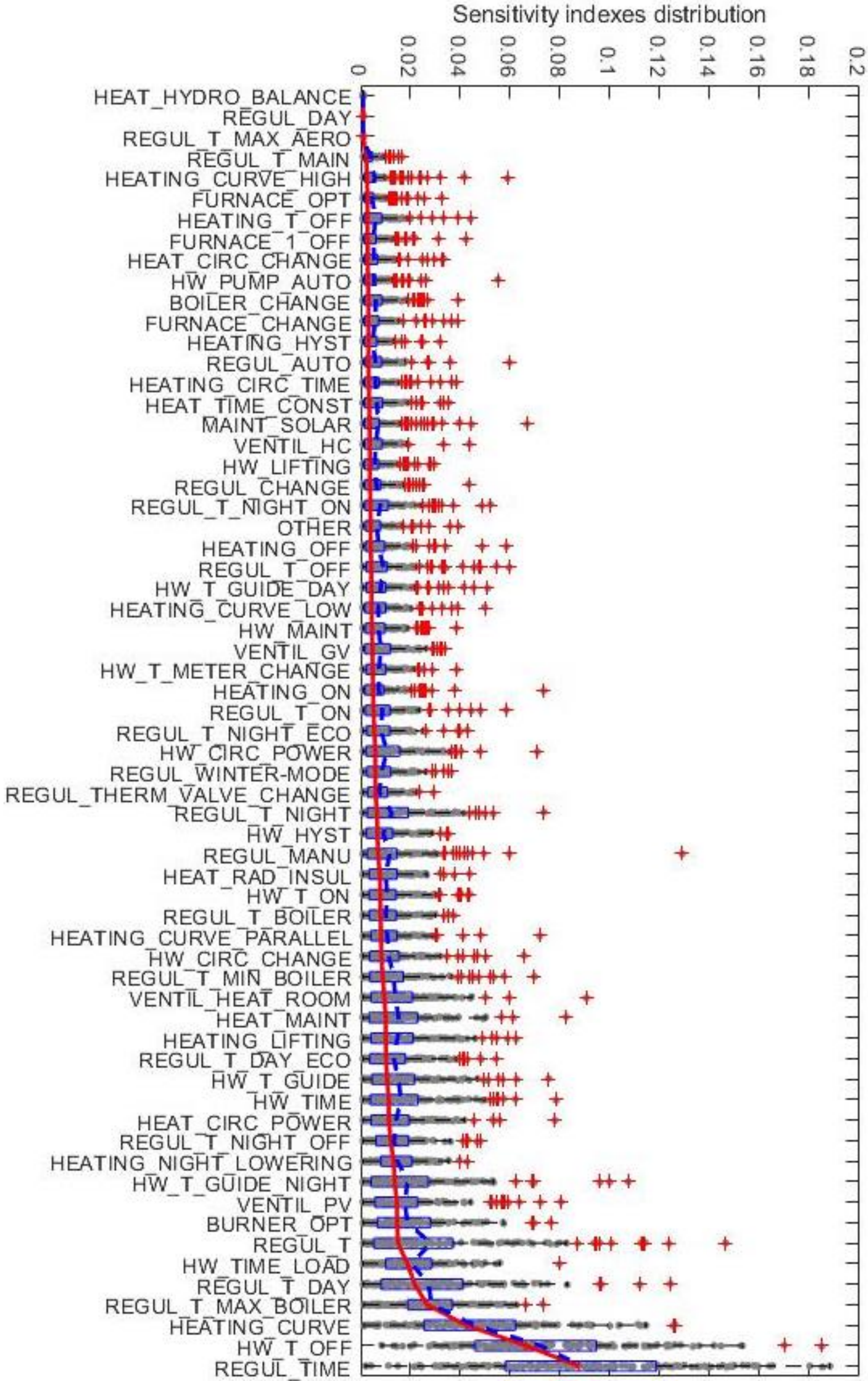

Figure 12 Distribution of first-order sensitivity indexes for each LICOM

4. *REGUL_T_MAX_BOILER*
   Maximum boiler setpoint temperature, in [°C]. It means changing the maximum setpoint temperature of the furnace. Therefore, it limits the furnace (e.g. at 75°C) instead of letting the furnace going up to 100°C e.g. The furnace burns at a more efficient and constant level.

5. *REGUL_T_DAY*
   Heating day setpoint temperature, in [°C]. E.g 22°C. This parameter is essential during a daily schedule when heating is switched on and during winter months. This represents the most frequent measures applied, even because it is easily accessible and often it is not optimized in the default settings.

It is important to specify that the identified five LICOMs are not the most effective in absolute terms, the highest indexes do not mean the highest energy savings. In the following stage of the project, a more quantitative analysis is required to identify trustable intervals of the most probable savings reachable by each LICOM.
Sensitivity analysis does not differentiate between positive and negative contributions to the final energy performances. Indeed, the computed indexes should be read as a quantitative measure describing the effects of each input (LICOM) on the output variability (energy savings).

6 Next steps

The project planning is characterized by a total of five macro-activities that can be summarized as follows:

1. **Database →** In this first stage a preprocessing of the energo database is required to identify the optimization measures of interest [4] and buildings with a robust tracking activity. Secondly, the dataset is integrated with the time evolution of five weather indicators, and organized following the time windows of interest.

2. **Residential building →** A more detailed dataset is used to analyze the energy performances of a building stock of residential buildings. This stage requires the adoption of the proposed regression model coupled with surrogate-based sensitivity analysis. It is worth specifying that the calibrated numerical model tries to simulate separately the effect of each LICOM and represents the key element on which all the subsequent numerical analyses are based.

3. **Quantitative analysis →** Following the computation of robust sensitivity indexes, a quantitative analysis of the energy savings is required in order to associate with each LICOM the most probable interval of energy saved (kwh). This interval must account for the uncertainty associated with the model itself and the weather conditions. Additional probabilistic analyses can be performed to identify conditional energy savings, for instance depending on a specific weather condition and/or performance targets.

4. **Non-residential buildings →** The proposed numerical model is tested with a different dataset representative of non-residential buildings (offices) that have other plant and energy needs. In this case, the dataset that will be used is characterized by different optimization measures with respect to the previous analysis due to scarce detailed data.
5. **A critical analysis →** Finally, the obtained results will be subject to a critical analysis moving the discussion to a more "practical" problem view. This stage aims at identifying any particular pattern or specificity that can provide directions towards a more effective energy optimization planning.

The working time required by each macro-activity is reported in the following Gantt Diagram (Figure 13) together with the activities planning of the whole project. After about one year the current project status is consistent with the initial planning, the next steps will focus on more quantitative analyses on the energy savings, tests on an alternative building stock and finally, a coherent critical analysis will be carried out.

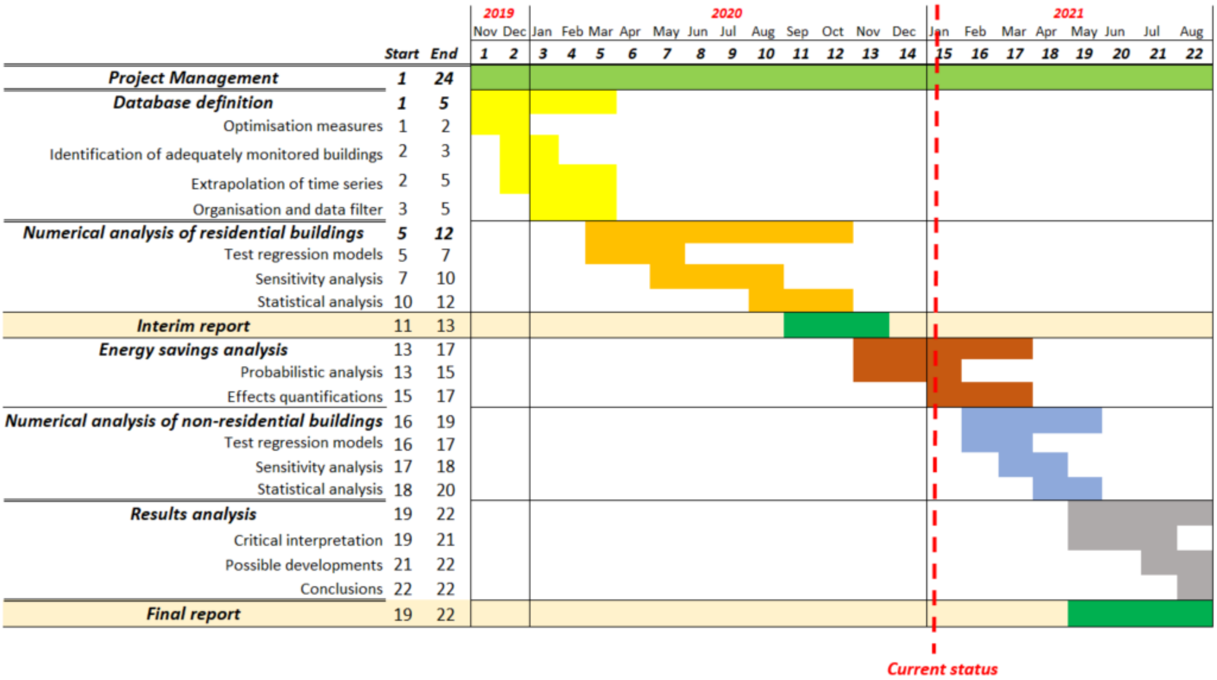

Figure 13 Activities planning

7 National and international cooperation

The scientific and technological results focus on the identification and definition of optimization measures with the greatest impact in terms of reducing energy consumption. The transfer of the results to the market is aimed at "*Accelerating the process of energy renovation of buildings through the large-scale implementation of optimization measures with the greatest return on investment*". This is possible with the implementation of support activities carried out during the project.

Support group
The coaching group must be able to assist the research team in transferring the results of the project to the market.
The Positive Gap project support group is composed of:

- RCVS engineer (Ing. Roland Connus) for the French-part of Switzerland ;
- Engineer RCVS (Ing. Andrea Andreoli) for Ticino ;
- Responsible for Energo French-part and Ticino (Joel Lazarus)
- Two Technicians, in charge of installations maintenance.

Two specific meetings have been held (26-27 February in Lausanne and 17-18 October in Lugano), obtaining very interesting feedback. The attention has been focused on the quality and reliability of the data, the identification and selection of LICOMs related to energy reduction events and, finally, the methodology validation.
Subsequently, the contribution of RVCS engineers and technicians will be used to better specify the nature of the measurements. In this way, it will be possible to check the work quality concerning the optimization measures and the related positive gap. The knowledge and practical experience of the support team will enable the definition of "*best practices*" for engineers and technicians in charge of building energy optimization.

Dissemination
Regarding the dissemination of the results, the first training course was held on 4.12.2019 for the technicians responsible for the operation of the public housing stock facilities in the municipality of Chiasso. There was a great interest in the energo database and the approach to the project's problems, as well as a strong need to identify the most effective low-cost measures leading towards a global energy consumption reduction. On 29 January 2021 a half-day of further training will be provided in the CAS Building Management course at SUPSI, during which the first results of the study and the innovative approach adopted will be shown.

Conferences/presentations
On the 3rd and 4th of September 2020, SUPSI in collaboration with Energo was selected to present the Positive Gap project at the Status Seminar organized by Brennet in Arau. During this conference, interesting comparisons and relations with other projects were made.

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